



Making do with less (data): Compressed Sensing in MRI

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Edinburgh Imaging
www.ed.ac.uk/edinburgh-imaging

Outline

Data acquisition in MRI

Undersampling

Compressed Sensing in MRI

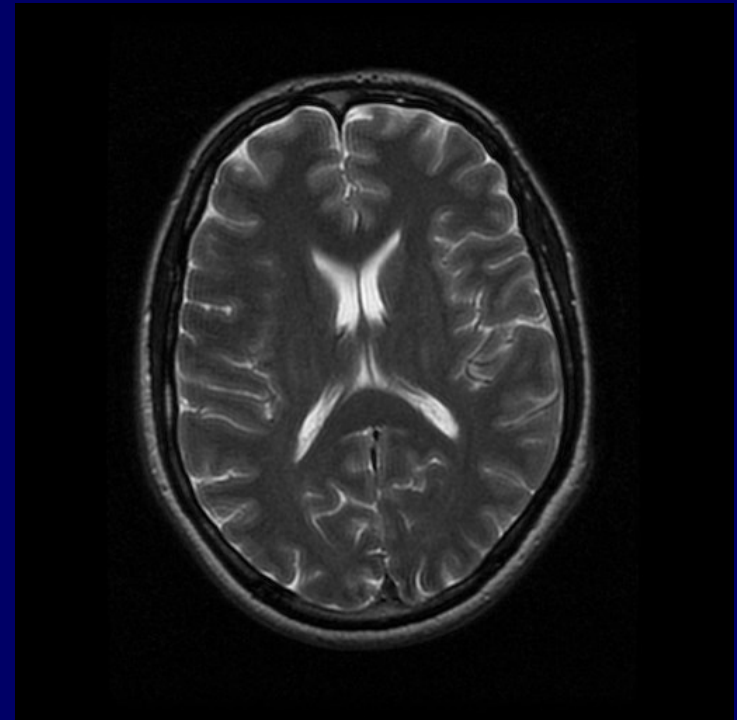
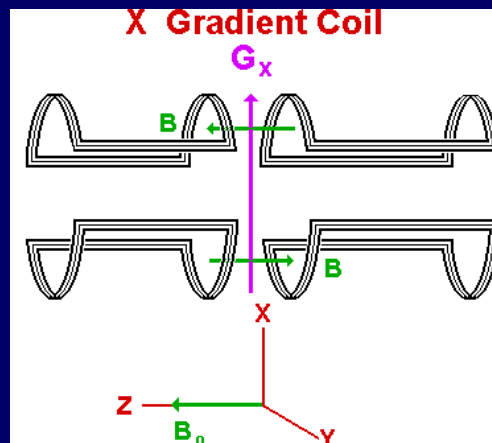
Practical issues

Applications

Mike Davies, Engineering

Spatially localised NMR = MRI

Lauterbur 1973 and Mansfield 1973



MRI acquisition

Excite

Evolve

Acquire

MRI acquisition

repeat

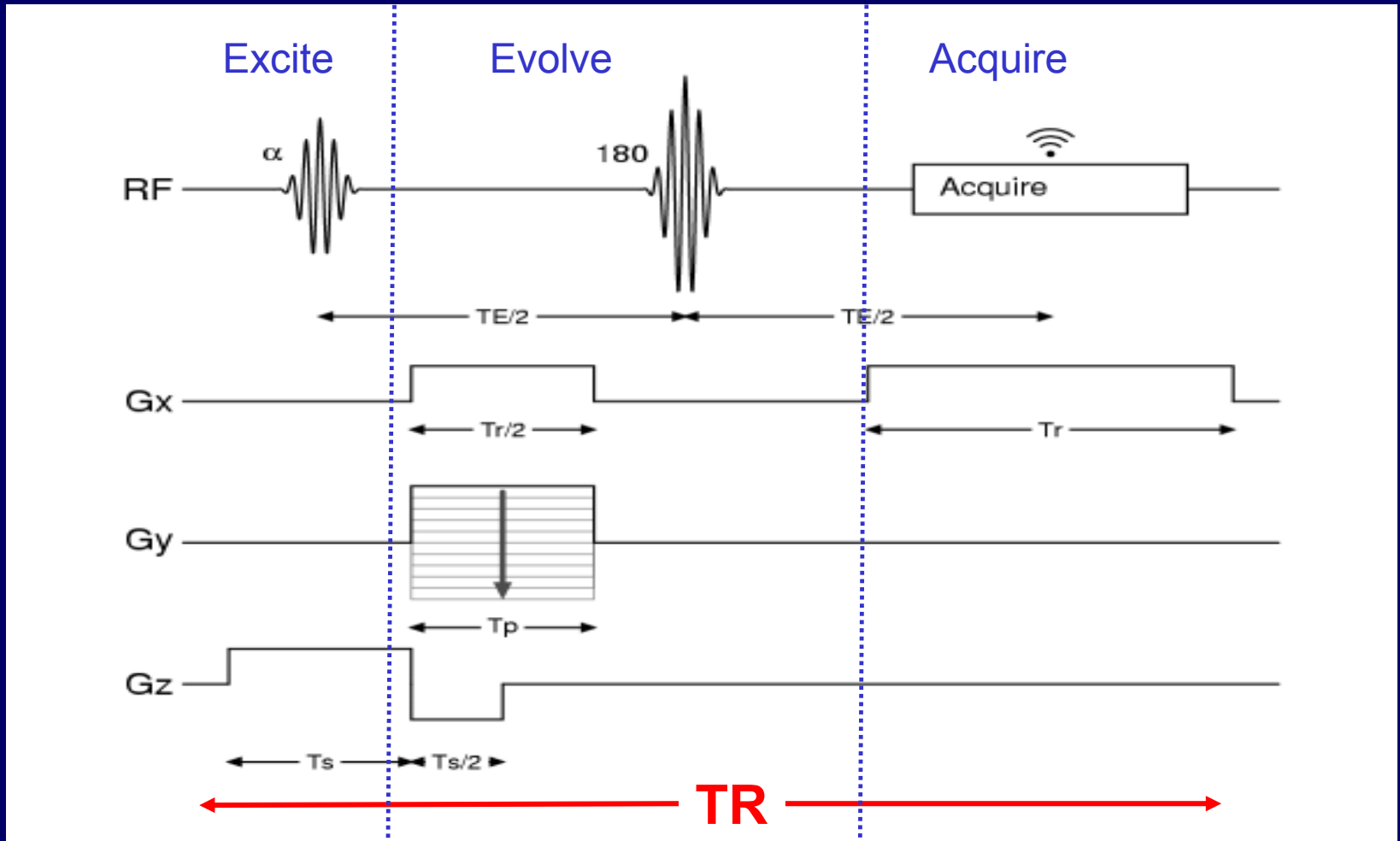
Excite

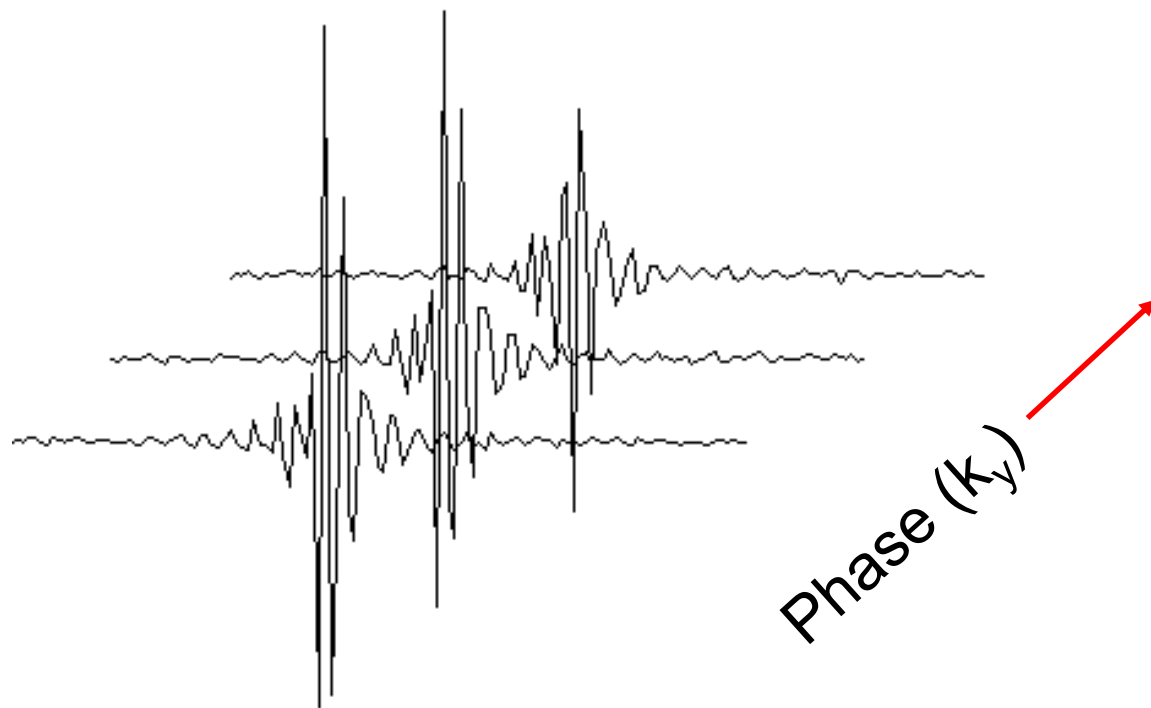
Evolve

Acquire

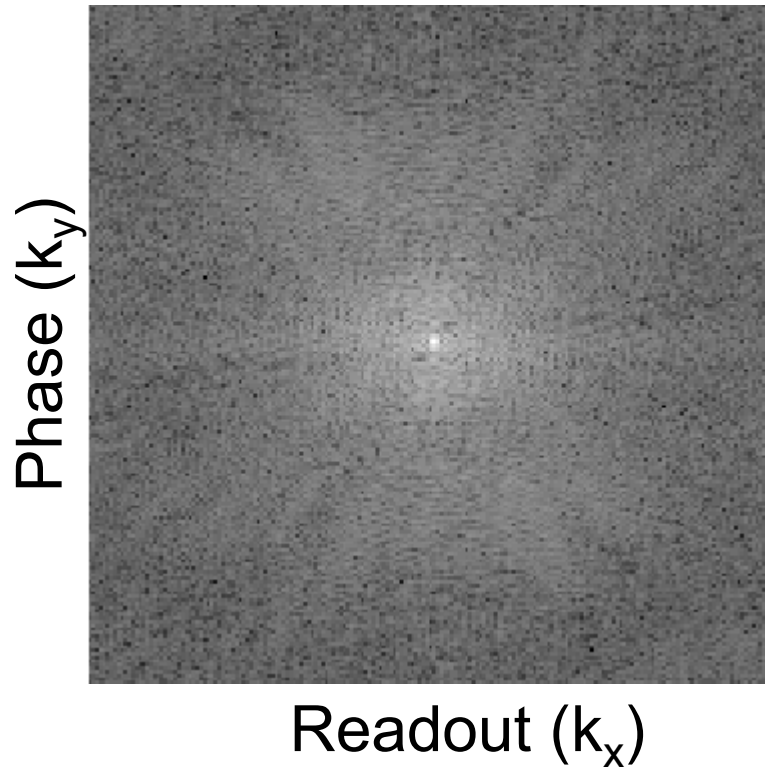
until spatially encoded

MRI acquisition

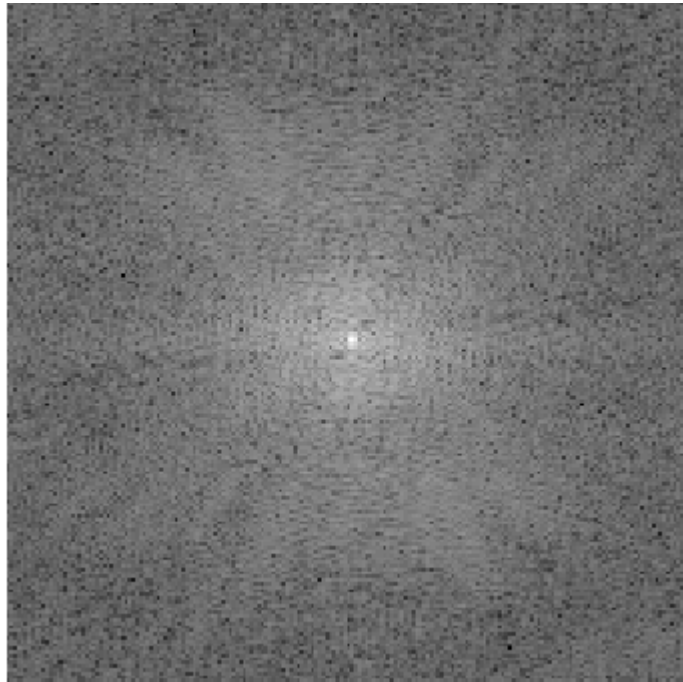




Acquired signals



k-space



k-space

FT
→

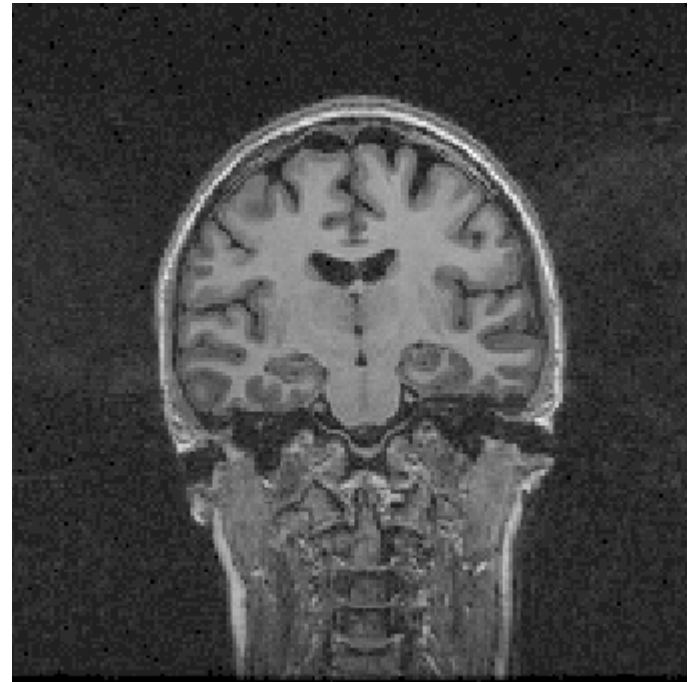
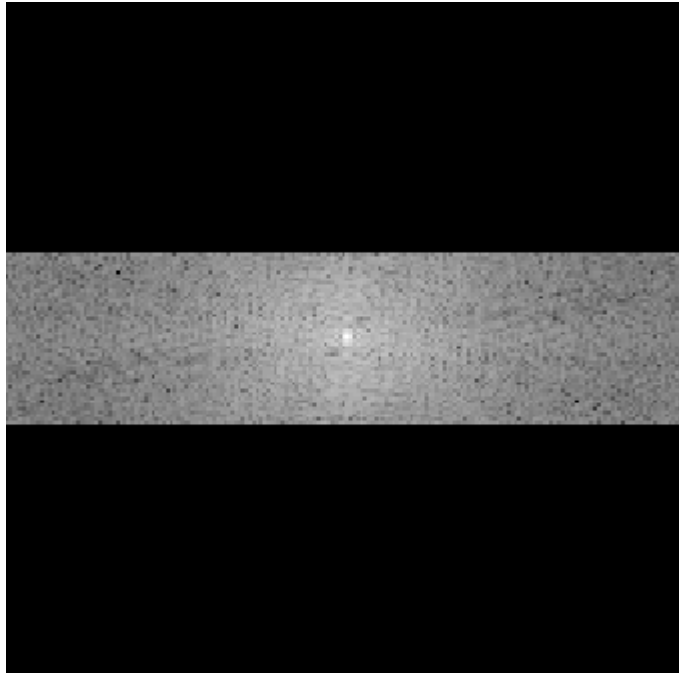


image space



k-space

FT
→

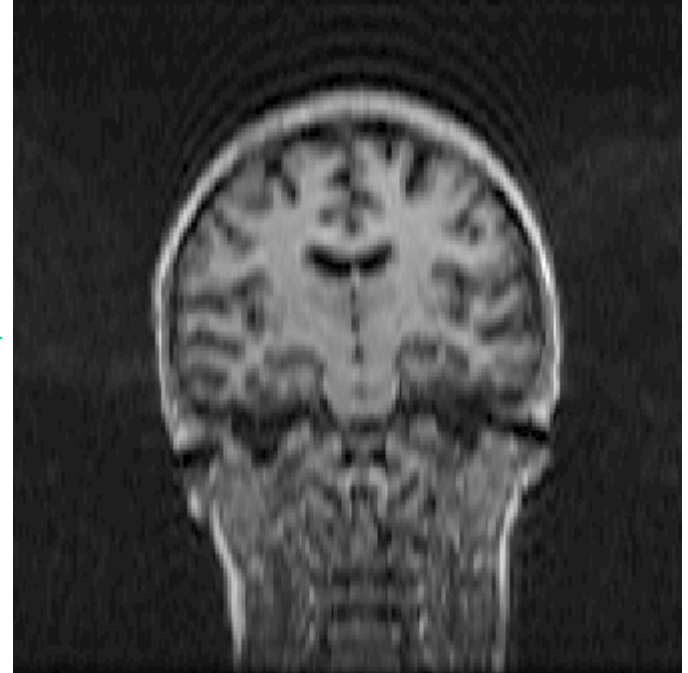
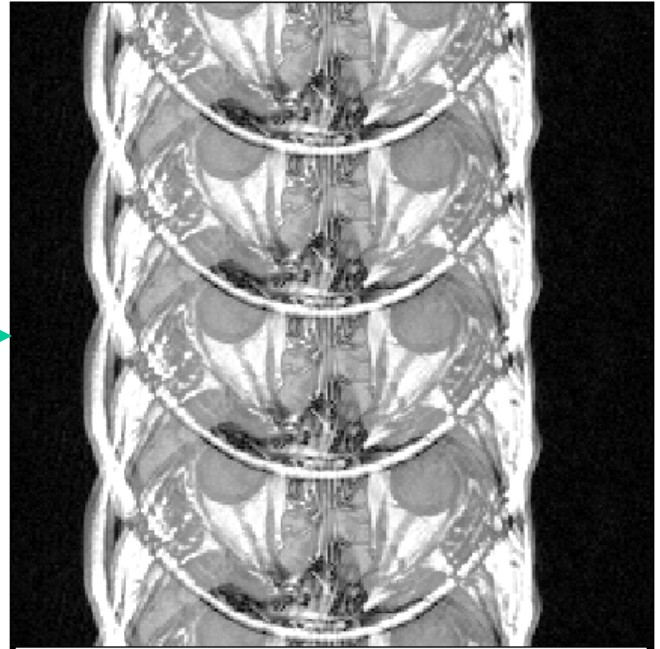
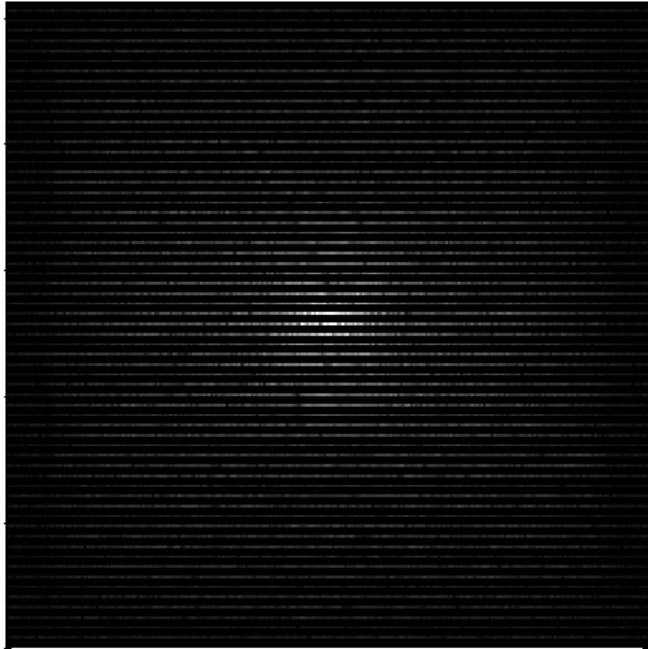


image space



Is there a better way?

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Most images are 'sparse'

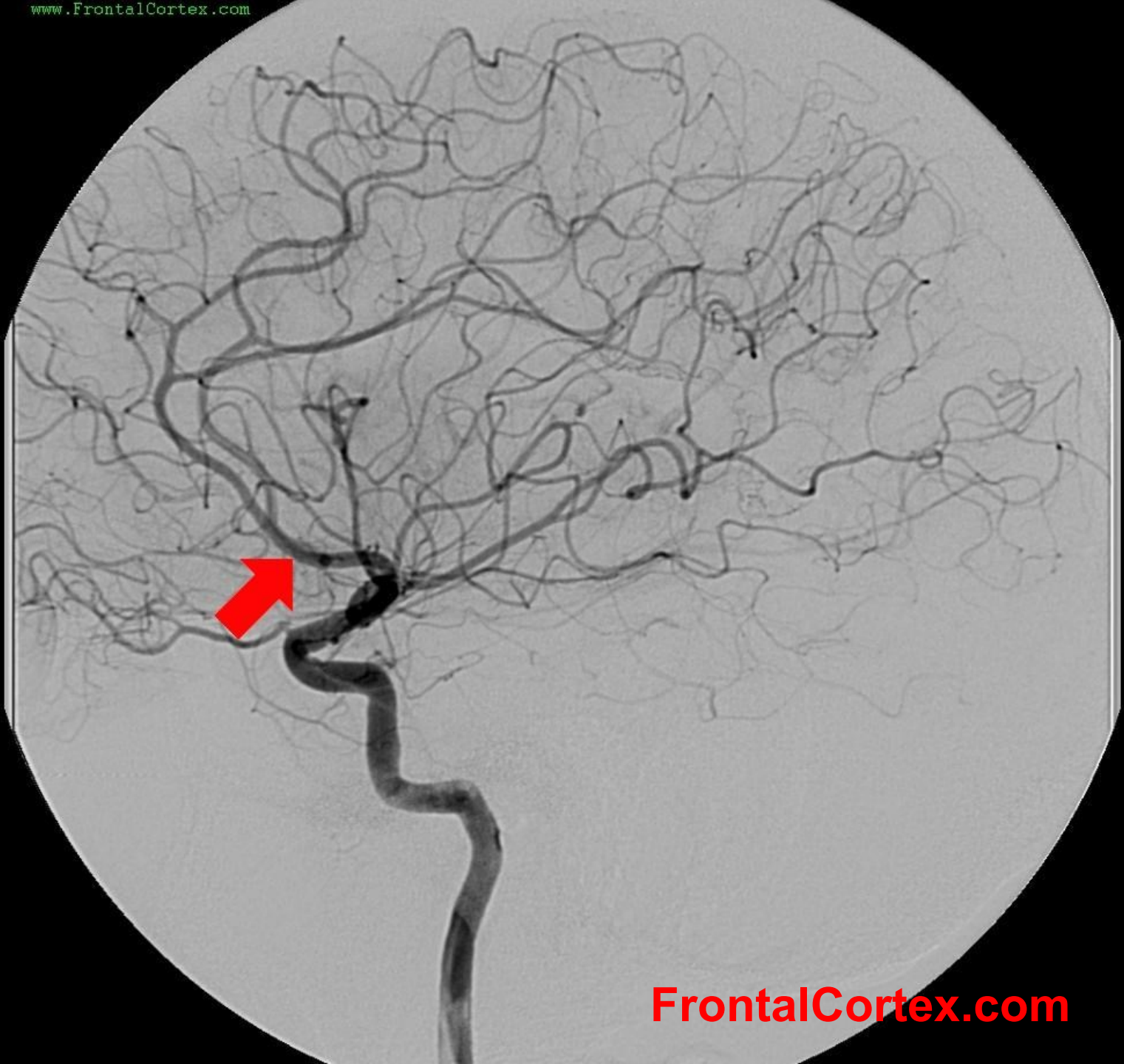
Data compression (JPEG, MPEG)

Is there a better way?

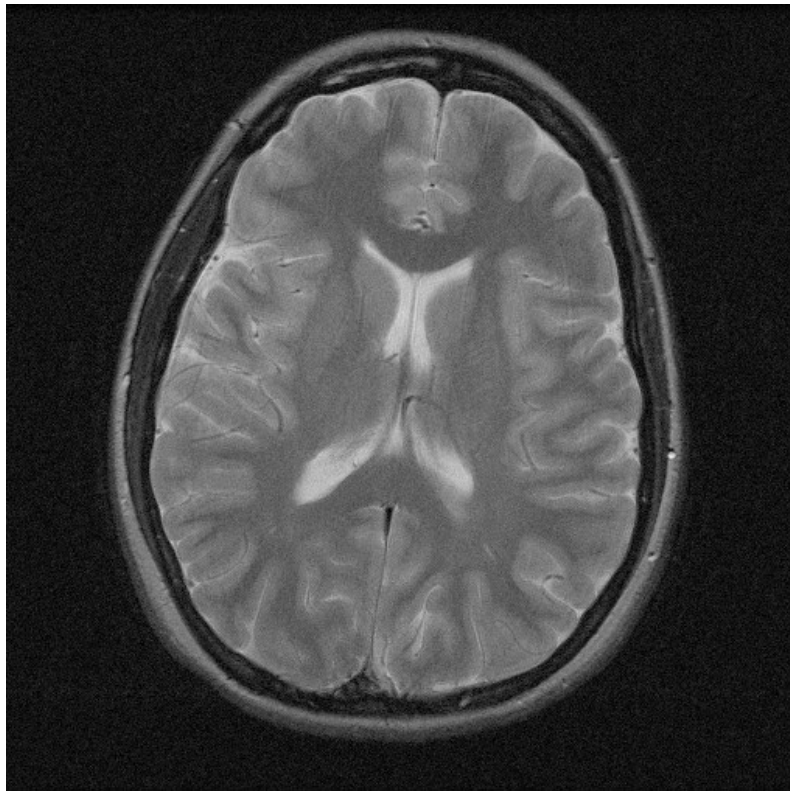
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Data compression (JPEG, MPEG)

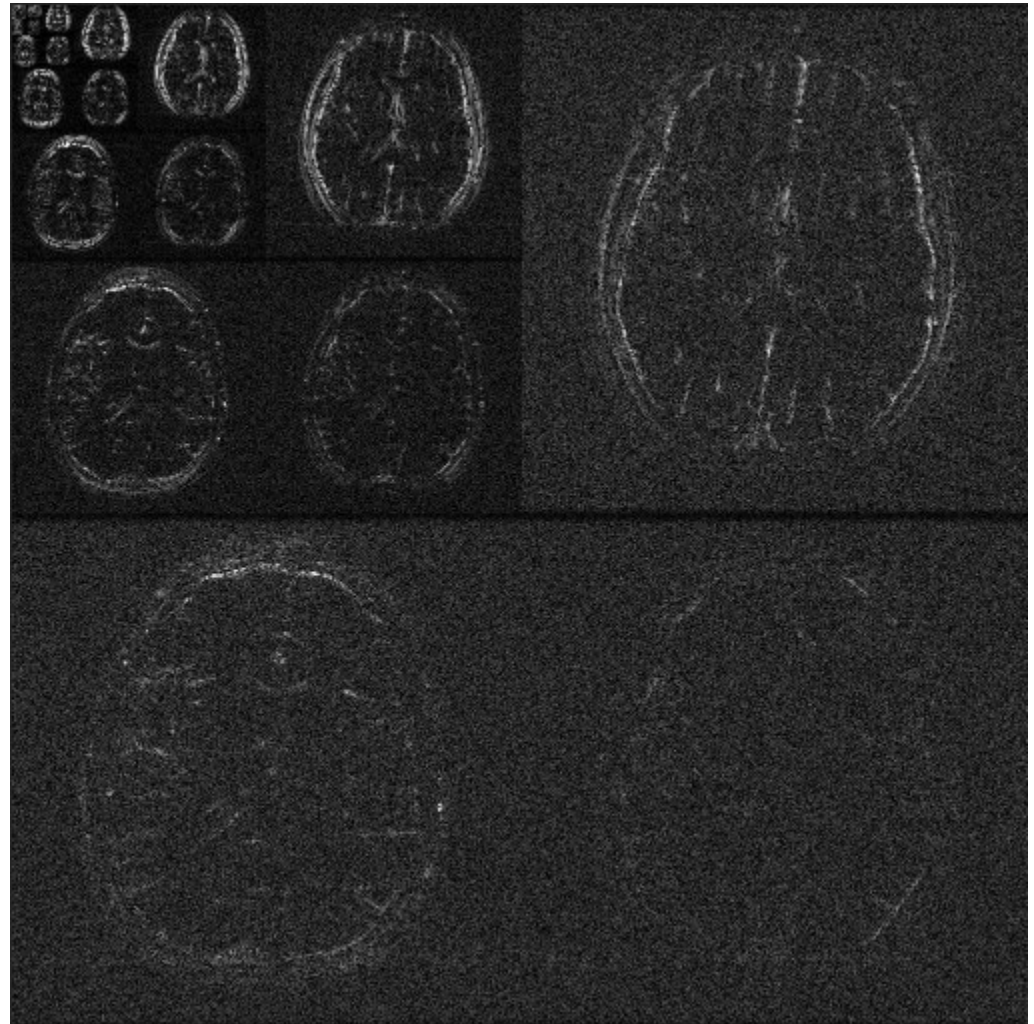
**If you don't need the data,
why collect it?**



T2w brain image



Wavelet transform



Compressed Sensing

Candes 2006, Donoho 2006
IEEE Trans Inf Theory

Lustig *Magn Reson Med* 2007

Compressed Sensing

Candes 2006, Donoho 2006
IEEE Trans Inf Theory

Lustig *Magn Reson Med* 2007

Sparsity

Randomly undersampled data

Nonlinear reconstruction

<http://www.eecs.berkeley.edu/~mlustig/>

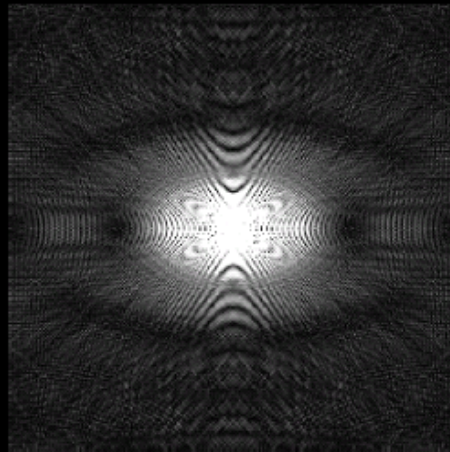
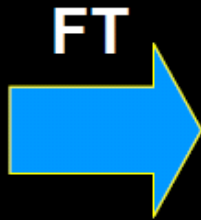


X

<http://www.eecs.berkeley.edu/~mlustig/>



X



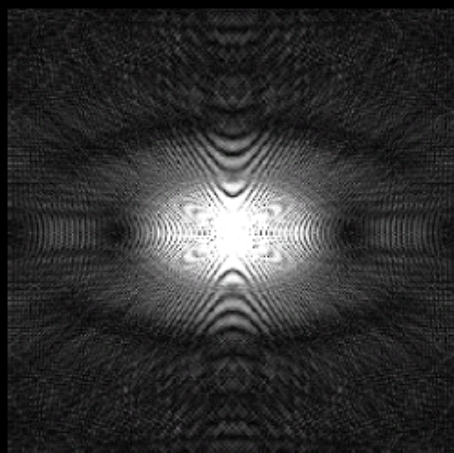
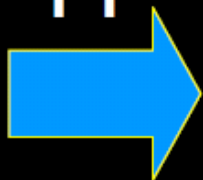
FX

<http://www.eecs.berkeley.edu/~mlustig/>



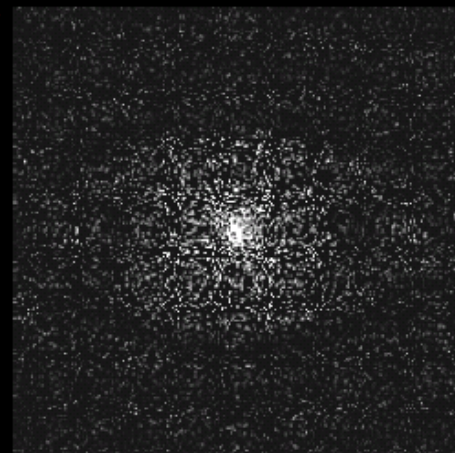
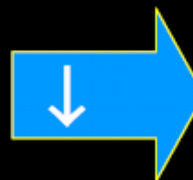
X

FT



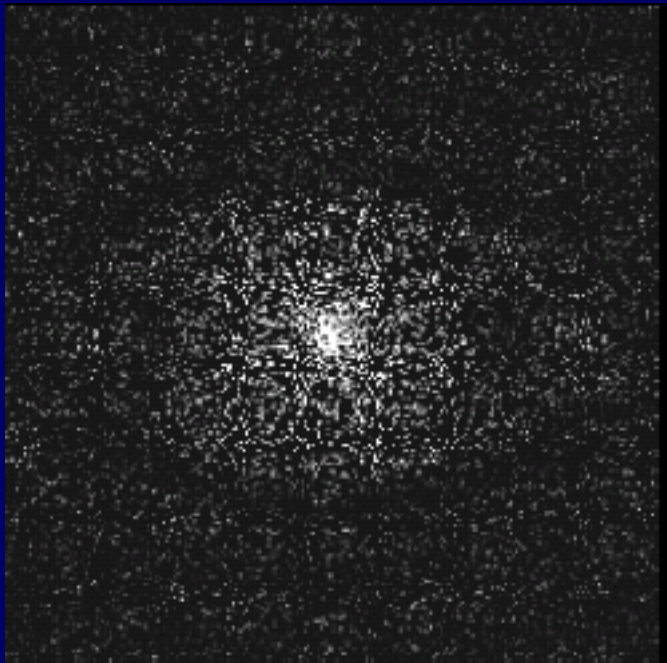
FX

**Randomly throw
away 83% of
samples**



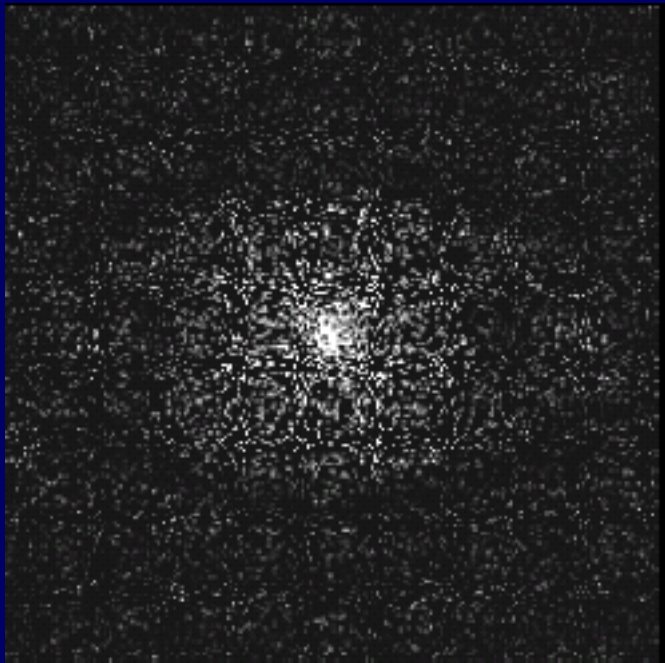
UFX

$$\mathbf{Y} = \mathbf{U} \mathbf{F} \mathbf{X}$$



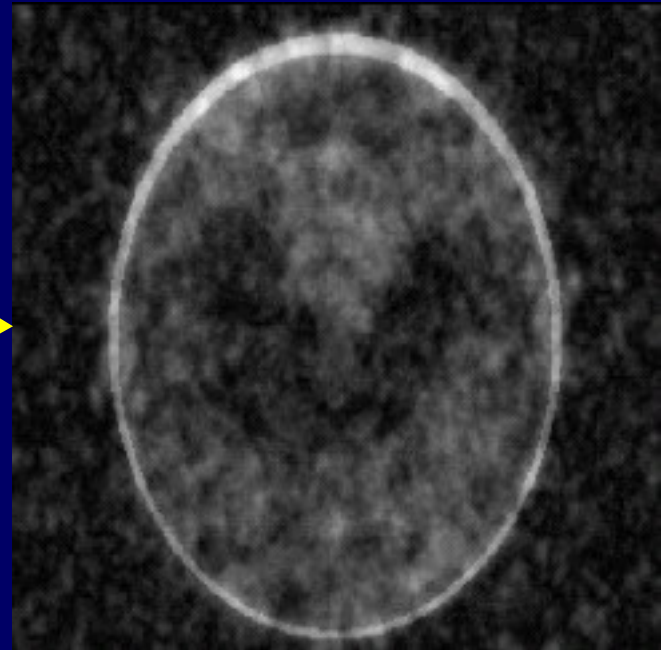
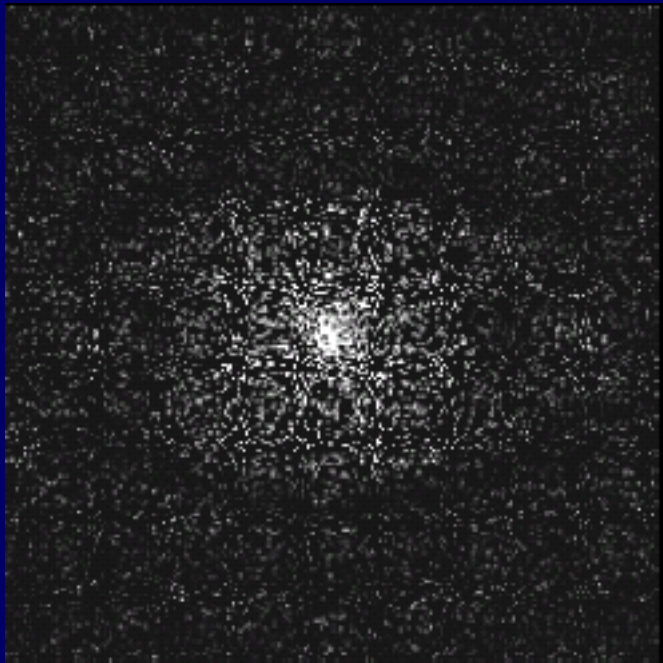
$$\mathbf{Y} = \mathbf{U} \mathbf{F} \mathbf{X}$$

$$\|\mathbf{Y} - \mathbf{U} \mathbf{F} \mathbf{X}\|^2 < \varepsilon \quad (\text{Least Squares})$$



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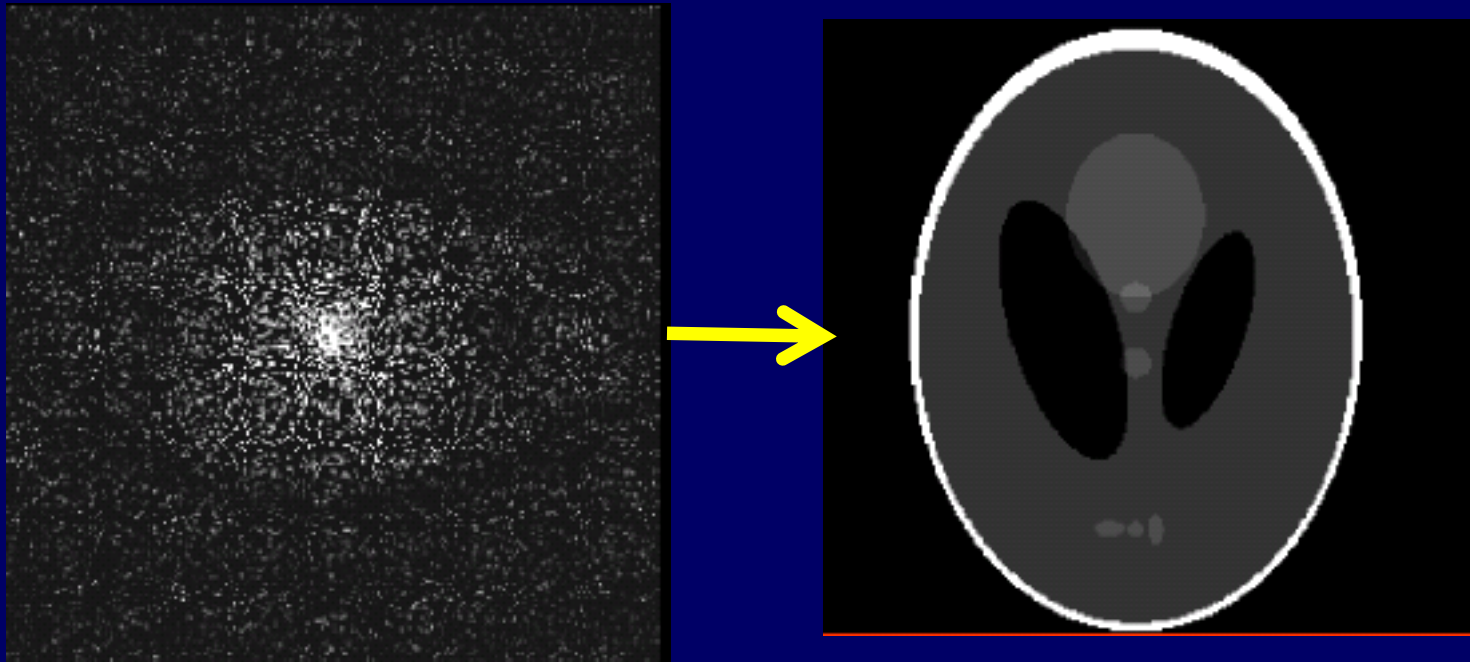


Compressed Sensing

Minimise $\|Q X\|_1$ (sparsity)

subject to...

$\|Y - U F X\|^2 < \varepsilon$ (data consistency)



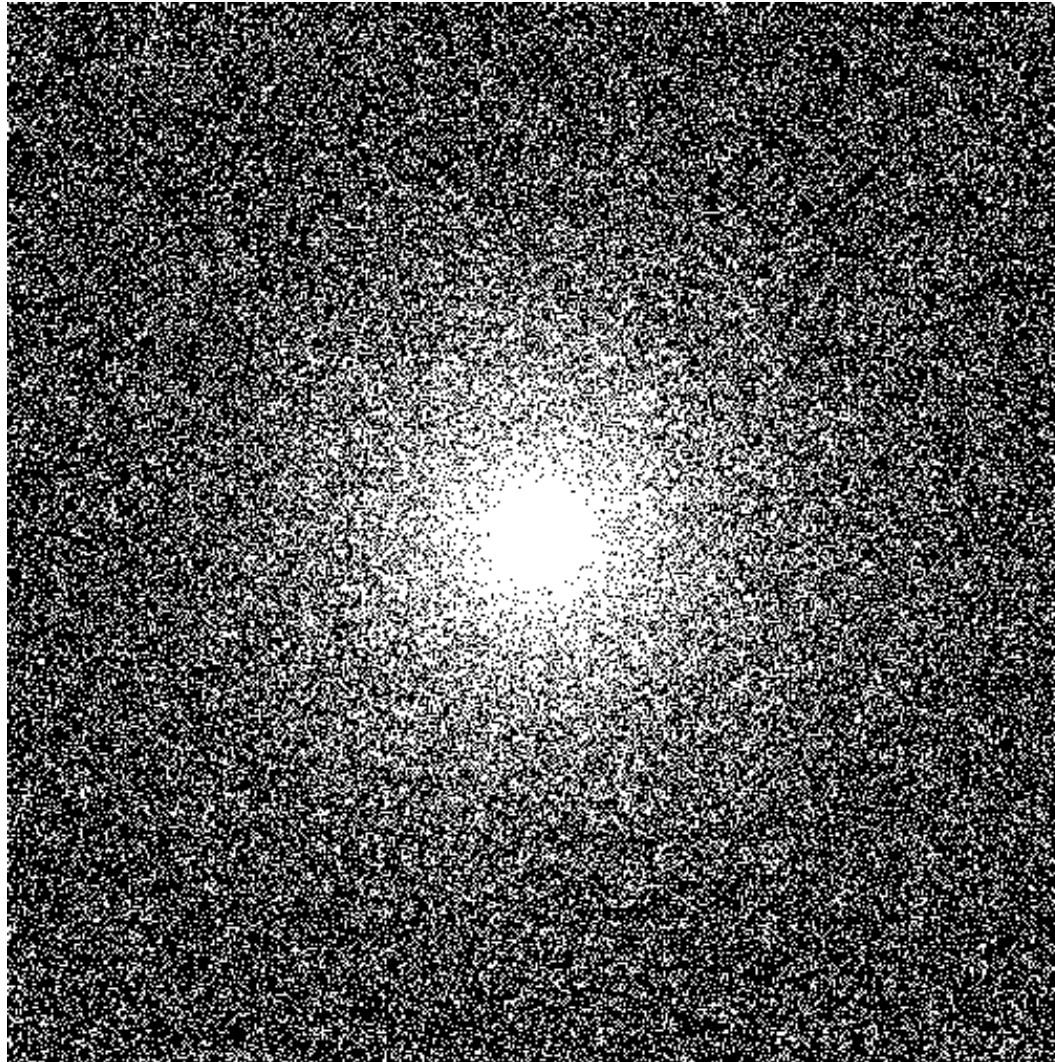
“...the results are surprising” (Candes 2006)

Minimise the objective function...

$$\{ ||\mathbf{W} \mathbf{X}||_1 + \lambda ||\mathbf{Y} - \mathbf{U} \mathbf{F} \mathbf{X}||^2 \}$$

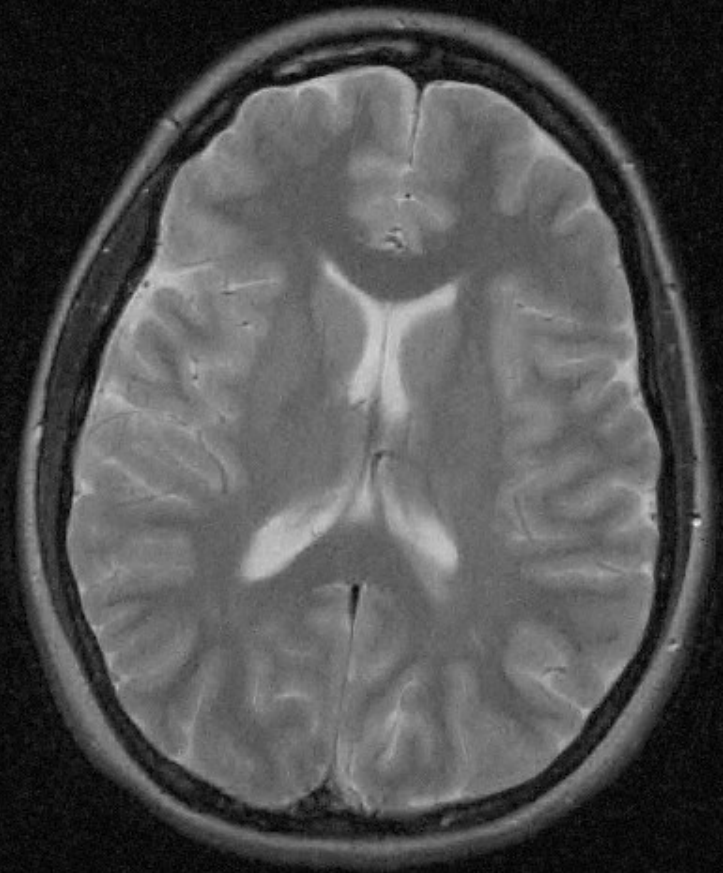
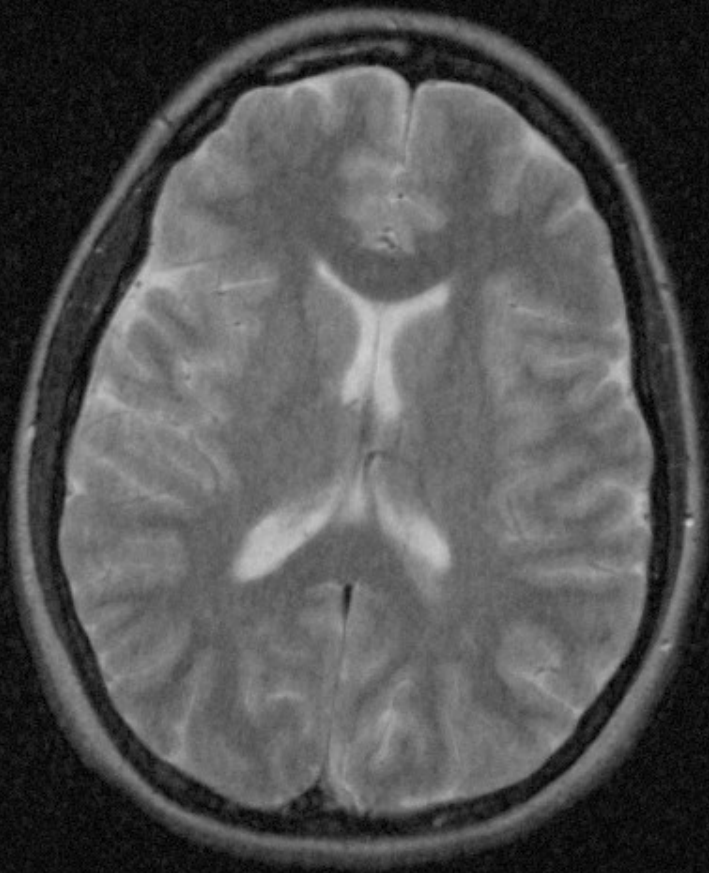
Iterative solution

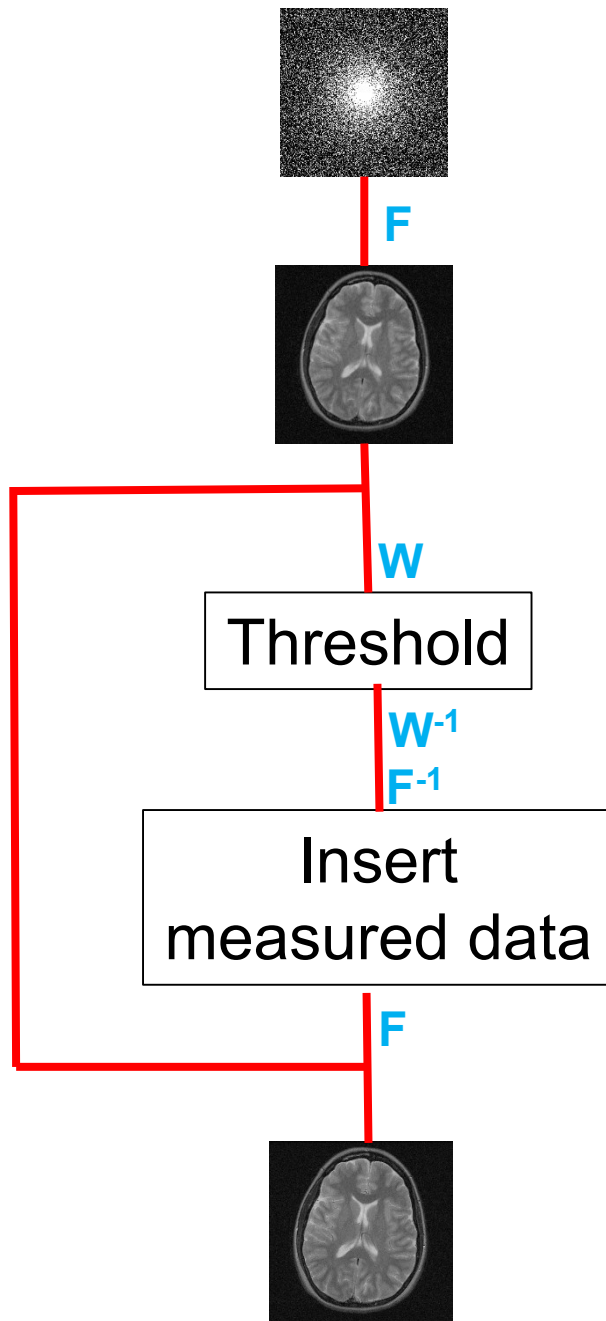
3 times undersampling mask



Linear recon

CS recon





Enforce sparsity in W-domain

Data consistency in k-space

But...

We can't undersample in k_x

1D undersampling doesn't work well

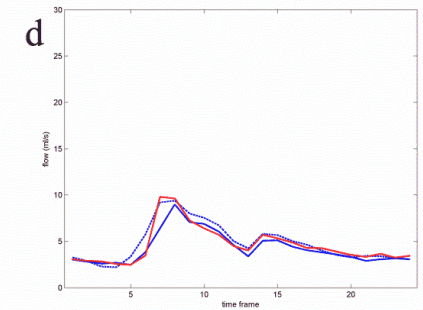
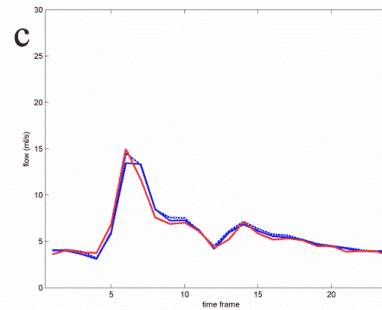
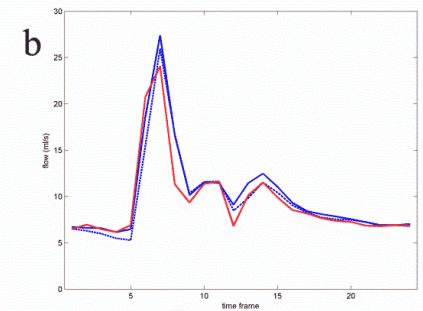
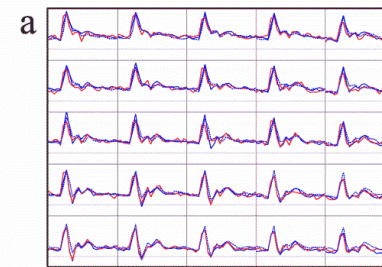
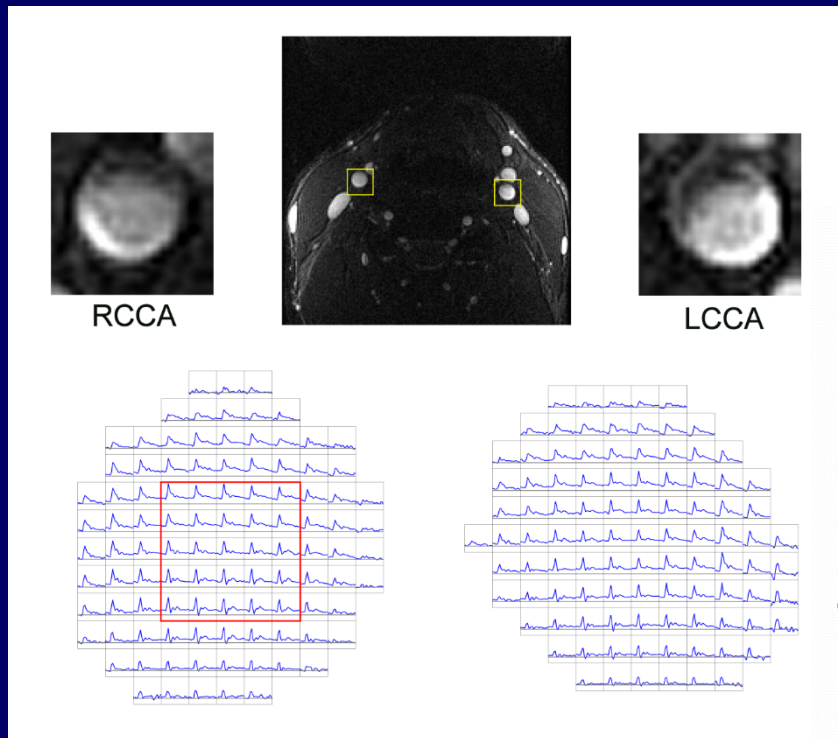
2D undersampling pattern is critical

Applications

Need to undersample
in 2 or more dimensions

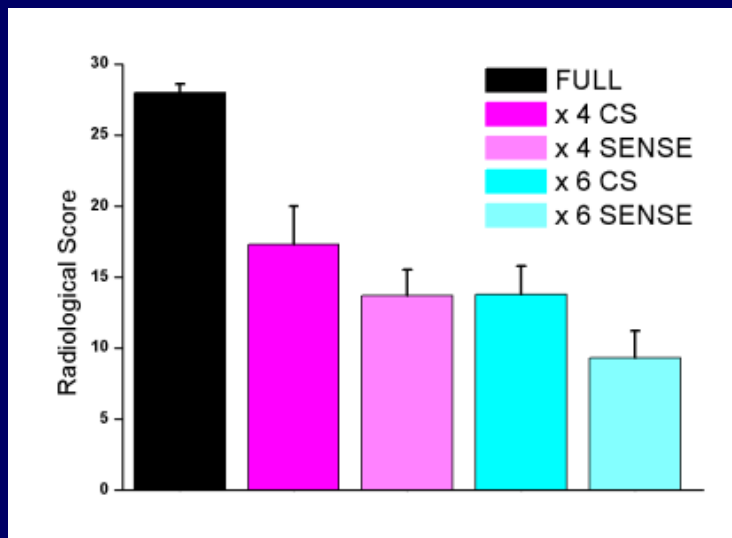
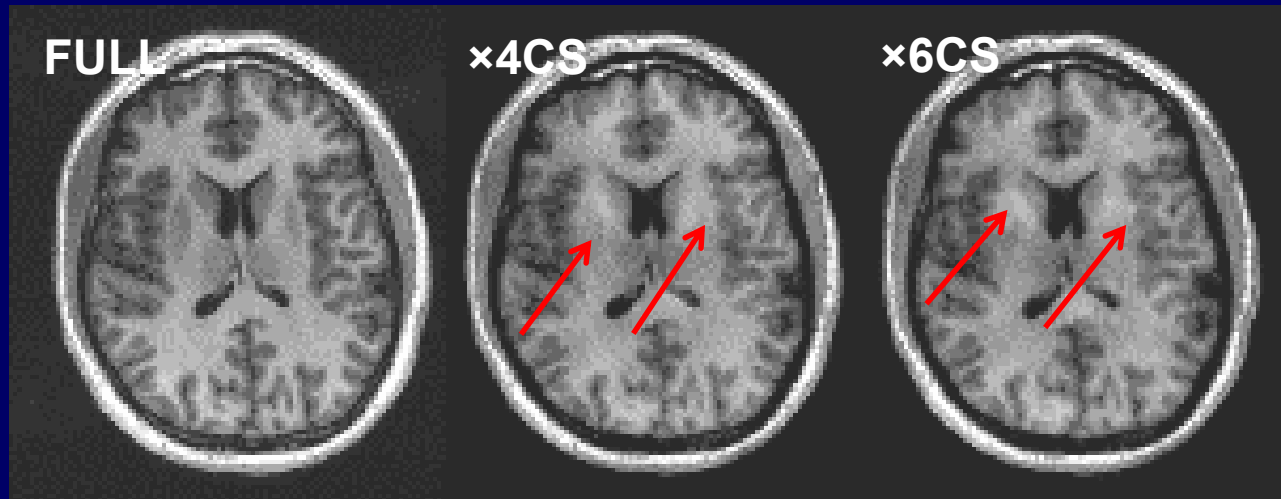
Standard 2D Brain	-
3D brain	+
Multiparameter 2D brain	+
Cardiac	+
Blood flow	+

Carotid blood flow



Tao et al, *Magn Reson Imag* 2013

UNDERSAMPLED 3D BRAIN IMAGES



ISMIRM 2015, #2497

Current work

Quantitative parameter mapping

Multichannel data

Non-equilibrium sequences

Mike Davies

Arnold Benjamin

Wajiha Bano

Zaid bin Mahbub

Mo Golbabaee

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